Renewable and Sustainable Energy Reviews 36 (2014) 270–276

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

Adaptive neuro-fuzzy generalization of wind turbine wake added turbulence models

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ARTICLE INFO

Article history:
Received 29 January 2014
Received in revised form
8 April 2014
Accepted 27 April 2014
Available online 20 May 2014

Keywords:
Wind energy
Wake wind speed
Turbulence model
Wake added turbulence
Adaptive neuro-fuzzy system (ANFIS)

ABSTRACT

When the turbine extracts power from the wind, a wake evolves downstream of the turbine. The turbines operating in the wake are not only subjected to a decreased wind speed but also increased dynamic loading arising from the increased turbulence induced by the upstream turbines. This increased turbulence must be accounted, when selecting a turbine. This increase in turbulence intensity can imply a significant reduction in the fatigue lifetime of wind turbines placed in wakes. For this reason, a large number of studies have been established concerning the calculation of wake added turbulence. Even though a number of mathematical functions have been proposed for modeling the wake added turbulence, there are still disadvantages of the models like very demanding in terms of calculation time. Artificial neural networks (ANN) can be used as alternative to analytical approach as ANN offers advantages such as no required knowledge of internal system parameters, compact solution for multi-variable problems and fast calculation. In this investigation adaptive neuro-fuzzy inference system (ANFIS), which is a specific type of the ANN family, was used to predict the wake added turbulence. Neural network in ANFIS adjusts parameters of membership function in the fuzzy logic of the fuzzy inference system (FIS). This intelligent algorithm is implemented using Matlab/Simulink and the performances are investigated. The simulation results presented in this paper show the effectiveness of the developed method.

Contents

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http://dx.doi.org/10.1016/j.rser.2014.04.064
1364-0321/

1. Introduction

Due to the cost of land and civil works, wind turbines tend to be positioned close to each other in wind farms, creating interference effects. Behind a wind turbine a wake is formed where the mean wind speed decreases slightly and the turbulence intensity increases significantly. This increase in turbulence intensity in wakes behind wind turbines can imply a significant reduction in the fatigue lifetime of wind turbines placed in wakes.

Turbines operating in wakes are affected to higher turbulence loading than turbines operating in the free wind. Appropriate turbulence calculations should be made before selecting the proper turbine design. The wake added turbulence may be calculated using different wake or turbulence models. These models are typically very different in detailing level and also in accuracy. The models range is from simple engineering models to the more advanced computational fluid dynamic (CFD) models. The CFD-models are typically also very demanding in terms of calculation time.

Turbulence has an important influence on the average output power of a wind turbine taken over a certain period of time. A method of predicting the influence of wind turbulence on the energy produced by a wind turbine was presented in [1]. It was shown that neglecting the coupled dynamic effects due to turbulence may result in over predictions of more than 10%. The wind dynamics is coupled to the turbine dynamic characteristics and results in a fairly complicated behavior. Thus, the common “static” model of calculating the average power, which is based on the turbine power curve and the average wind speed, may result in increasing errors. Paper [2] presented three different models for calculating the average output power, taking into account the dynamic characteristics of the phenomenon. The purpose of the present paper was to study the coupled influence of the wind turbulence and dynamic characteristics of the wind turbine system, on the average output power. It was shown that wind turbulence has an important influence on the average output power. Using the static value of the average power may result in increasing inaccuracy. An explicit algebraic model to calculate the wake characteristics, in particular the different components of the turbulent stress tensor, was developed in article [3]. The model is able to reproduce the six components of the symmetric stress tensor of a standard neutral atmosphere. This work was mainly dedicated to the study of non-isotropic characteristics of turbulence in wind turbine wakes, specifically the shear layer of the near wake. The paper [4] reported on a systematic study of the performance of a wide range of low-Reynolds number turbulence models used to predict the detailed flow characteristics of ramp-up-type unsteady flows in a channel. The aim of study [5] was to evaluate experimentally rotation and turbulence effects on a wind turbine blade aerodynamics, focusing particularly on stall mechanisms. Wind turbine wakes and the neutral atmospheric wind flow over complex terrain were investigated in paper [6] using the Computational Fluid Dynamics software Fluent. The velocity and turbulence results were examined at four down wind locations in the vertical and lateral directions. Study [7] experimentally investigated the effects of ambient turbulence on the wake flows and power production of a horizontal-axis wind turbine. In addition, the experimental results showed that the power productions in the grid-generated turbulent flows were slightly higher than that in the smooth flow. The computation in [8] revealed that the effect of turbulence created by the blades has high significance. The results in [9] showed that the influence of different turbulence models on the velocity field is less, on the pressure field is relatively large, and on the value of the total torque is much larger. In paper [10] the possible error/uncertainty introduced by applying the simple effective turbulence intensity model was investigated in two cases. Paper [11] presented approaches the modeling of the wind speed turbulence in a point on the rotating blade at a certain distance from the rotor axis. Paper [12] presented a practical approach to identify a global model of a wind turbine from operational data, while it operates in a turbulent wind field with a varying mean wind speed and under closed-loop control. The article [13] reviews the state-of-the-art numerical calculation of wind turbine wake aerodynamics.

Even though a number of mathematical functions have been proposed for modeling the wake added turbulence, there are still disadvantages of the models like very demanding in terms of calculation time. Artificial neural networks (ANN) can be used as alternative to analytical approach as ANN offers advantages such as no required knowledge of internal system parameters, compact solution for multi-variable problems and fact calculation [14–16]. In some investigations support vector regression (SVR) was used as alternative to analytical approach [17–20]. Mobile cloud computing has attracted attention in recent years for mobile cloud computing [21–24].

In this investigation adaptive neuro-fuzzy inference system (ANFIS) [25–29], which is a specific type of the ANN family, was used to predict the wake added turbulence. For the presently developed neural network, the wind turbines downstream distances were used as inputs. The ANFIS model is designed based on six analytical methods of calculating the wake added turbulence: Danish Recommendation (DR) [30], Frandsen and DIBt [31–33], Quarton [34], TNO Laboratory [35], Alternative Empirical Approach [36], Larsen [37,38]. In other words the ANFIS model should estimates average wake added turbulence based on the established analytical models.

ANFIS shows very good learning and prediction capabilities, which makes it an efficient tool to deal with encountered uncertainties in any system. The goal of the work [39] was to predict the daily performance of a ground-source heat pump system with the minimum data set based on an ANFIS. The simulation results shown that the ANFIS can be used in an alternative way in these systems. Papers [40,41] shown that the values predicted with the ANFIS, especially with the hybrid learning algorithm, can be used to predict the performance of the ground-coupled heat pump system quite accurately. ANFIS, as a hybrid intelligent system that enhances the ability to automatically learn and adapt, was used by researchers in various engineering systems [42–48]. So far, there are many studies of the application of ANFIS for estimation and real-time identification of many different systems [49–57].

2. The turbulence calculation

When calculating the design, lifetime and fatigue on wind turbines, the turbulence levels are of the most importance. The turbulence intensity is defined as the ratio between the standard deviation of the wind speed, σ_U, and the 10-min mean wind speed, U_{10}. When dealing with wind turbine wakes, it is tradition to

Table 1
Roughness length and wind gradient exponent.

Roughness class	Roughness length	Wind gradient exponent
0	0.0002	0.1
1	0.03	0.15
2	0.1	0.2
3	0.4	0.3

relate the 10-min mean wind speed to the free wind speed, i.e. the wind speed outside the wake.

$$I_T = \frac{\sigma_U}{U_{10}} \quad (1)$$

Assuming that the wind flow is a horizontally homogeneous, then the standard deviation of the wind speed process is only depended of the height above the terrain, x. The turbulence intensity in the height x meters is defined as:

$$I_T(x) = \frac{\sigma_U(x)}{U_{10}(x)} \frac{\sigma_U}{U_{10}} \quad (2)$$

where $I_T(x)$ is the turbulence intensity, $\sigma_U(x)$ is the standard deviation of the wind speed, $U_{10}(x)$ is the mean wind speed averaged over 10 min.

Experimental data has shown that the standard deviation of the wind speed only decreases very slowly. In [58,59], it is said, that it is reasonable to use constant standard deviations up to about the half-height of the internal boundary layer. Using this assumption, the vertical scaling of turbulence intensity between two heights is simply calculated by assuming the same standard deviations in the two heights (x and y meters).

$$\sigma_U(x) = \sigma_U(y) \frac{\sigma_U}{U_{10}} \quad (3)$$

$$I_T(x) U_{10}(x) = I_T(y) U_{10}(y) \frac{\sigma_U}{U_{10}} \quad (4)$$

$$I_T(y) = \frac{U_{10}(x)}{U_{10}(y)} I_T(x) \frac{\sigma_U}{U_{10}} \quad (5)$$

So now the problem is reduced into calculating the mean wind speed in the new height. The vertical scaling of wind speeds may be done using the power law vertical wind profile:

$$U_{10}(y) = U_{10}(x) \left[\frac{x}{y}\right]^{\gamma} \frac{\sigma_U}{U_{10}} \quad (6)$$

where γ is the wind gradient exponent.

The wind gradient exponent is known to be very depended on the roughness length or the roughness class. Table 1 below gives guidelines for selecting the wind gradient exponent if no measured data is available.

Inserting Eq. (6) into (5) we obtain the turbulence scaling law, valid for homogeneous terrain:

$$I_T(y) = \frac{U_{10}(x)}{U_{10}(y)} I_T(x) = U_{10}(x) I_T(x) \left[\frac{x}{y}\right]^{-\gamma} \frac{\sigma_U}{U_{10}} \quad (7)$$

2.1. Turbulence from wind turbine wakes

The wake added turbulence is either derived from the wake models that include turbulence modelling or from dedicated turbulence models. The turbulence calculated from the different models may be parameterized in numerous ways. The turbulence model must be used in connection with a wake model to take the reduced wind speeds in the wind farm into account. The results from the turbulence models may be classified in four categories:

1. Added turbulence model—calculated for the wake after a single turbulence
2. Added turbulence model—calculated for all surrounding turbines
3. Total turbulence model—calculated for the wake after a single turbulence
4. Total turbulence model—calculated for all surrounding turbines.

Models (1) and (2) give the wake added turbulence contribution. This should be added to the ambient turbulence level. The model type (3) gives the total turbulence level for a given wake at a given position (ambient and wake added), and this must be summed into a combined effect considering all upstream turbines. The model type (4) gives the total turbulence level in an integrated manner, thus no single wake adding is needed.

2.1.1. Partial wakes—Turbulence

When the turbine operates in a partial wake, we use Eq. (8) to calculate the added turbulence level considering the rotor area with ambient turbulence only. A linear weighting with rotor areas is assumed. The total turbulence intensity is calculated from

$$I_{total} = \sqrt{(I_{ambient})^2 + (I_{park})^2} \quad (8)$$

2.2. Turbulence models

2.2.1. Danish Recommendation (DR)

The Danish Recommendation [30] from 1992 specifies a quite simple wake added turbulence model. If the turbines are erected in a cluster with a minimum distance between the turbines of 5 times the rotor diameter or in a row with the distance 3 times the rotor diameter then a added turbulence intensity of $I_{\text{park}}=0.15$ can be used. An alternative is to use the mean-contribution, which varies by the mean wind speed and the distance between the turbines:

$$I_{park} = \beta_v \beta_l 0.15 \frac{\sigma_U}{U_{10}} \quad (9)$$

where β_v is a parameter taking the mean wind speed into account, β_l is a parameter taking the distance between the turbines into account. The β_l parameters are dependent on the geometrical configuration of the wind farm.

2.2.2. Frandsen and DIBt

Frandsen and Thøgersen [31] report an empirical turbulence model for calculating the integrated wake effect of turbines. This model takes into account the different structural fatigue responses of the structural materials considered, e.g. steel in the towers and hub extenders and glass fibre reinforced polyester (GRP) or glass fibre reinforced epoxy (GRE) in the blades. The equations below assume that the wind direction is approximately uniform distributed. Reference is made to Frandsen and Thøgersen [31] and Guidelines for the Design of Wind Turbines [32]. This model is included as a recommended model in the German DIBt Richtlinie [33]. The total turbulence intensity is determined from:

$$I_{T,total} = \left[(1 - N \times p_w) I_T^m + p_w \sum_{i=1}^{N} I_{T,w}^m \times s_i \right]^{1/m} \frac{\sigma_U}{U_{10}} \quad (10)$$

$$I_{T,w} = \sqrt{\frac{1}{[1.5 + 0.3 \times s_i \sqrt{v}]^2} + I_T^2} \frac{\sigma_U}{U_{10}} \quad (11)$$

where $p_w=0.06$ (probability of wake condition), $s_i=x_i/RD$, N is the number of closest neighboring wind turbines, m is the Wohler curve exponent of the considered material, v is the free flow mean

Table 2
Parameters for the Quarton and TNO turbulence models.

Turbulence models	K_1	α_1	α_2	α_3
Quarton and Ainslie (original)	4.800	0.700	0.680	−0.570
Quarton and Ainslie (modified)	5.700	0.700	0.680	−0.960
Dutch TNO laboratory	1.310	0.700	0.680	−0.960

wind speed at hub height, x_i is the distance to the ith turbine, RD is the rotor diameter, I_T is the ambient turbulence intensity (free flow), $I_{T,w}$ is the maximum turbulence intensity at hub height in the center of the wake.

2.2.3. D.C. Quarton and TNO laboratory

A simple equation to determine the wake added turbulence has been proposed by Quarton and Ainslie [34]. The parameters in the equation have been re-calibrated by Quarton and Ainslie (the modified values) and also the Dutch TNO laboratory [35]. The main form of the equation is

$$I_{add} = K_1 \times C_T^{\alpha_1} \times I_{amb}^{\alpha_2} \times (X/X_n)^{\alpha_3} \frac{\sigma_U}{U_{10}} \tag{12}$$

where K_1 is a proportionality constant, α_1, α_2, α_3 are exponents, X is the downstream distance (in meters), X_n is the length of the near wake (see the chapter on the eddy viscosity wake model), I_{amb} is the ambient turbulence.

The proportionally constant and exponents are determined from the table below. Based on wind tunnel test, Quarton proposed an alternative to his original model. The values of the parameters are given for the different models in Table 2.

2.2.4. Alternative empirical approach

Another alternative empirical characterization of the wake turbulence was proposed by Quarton and Ainslie [36]. Their equation is based on a parameterization on the near wake length which is primarily used in relation with the Eddy Viscosity model. They report, that the empirical turbulence decay is somewhat higher than other model predictions. The equation is:

$$I_{add} = 4.8 \times C_T^{0.7} \times I_{amb}^{0.68} \times (X/X_n)^{-0.57} \frac{\sigma_U}{U_{10}} \tag{13}$$

where I_{add} is the added turbulence intensity from the wind turbine wake, I_{amb} is the ambient wind speed, X is the downstream distance, X_n is the near wake length.

2.2.5. G.C. Larsen

The Larsen [37,38] is a simple empirical equation to determine the turbulence level within the wake. At positions downstream of the turbine, the wake added turbulence intensity can be determined from the equation:

$$I_w = 0.29 \times S^{-1/3} \sqrt{1 - \sqrt{1 - C_T}} \frac{\sigma_U}{U_{10}} \tag{14}$$

where S is spacing expressed in rotor diameters, C_T is the thrust coefficient.

The expression for turbulence intensity is only valid for distances larger than two rotor diameters downstream.

2.3. Validation of the turbulence models

As can be seen in Fig. 1, the Frandsen/DIBt model, Larsen model and Danish Recommendation model yield high values for the generated turbulence for downstream distances larger than 5D. The line corresponding to the alternative Quarton model cannot be seen, as the values are almost identical to the values of the TNO model; both yield very high values for the generated turbulence for distances smaller than 3D. All these models for the added turbulence have in common that they result in a constant turbulence intensity throughout the wake at a certain distance downstream of the turbine. However, in reality most turbulence is generated near the hub region and at the blade tips.

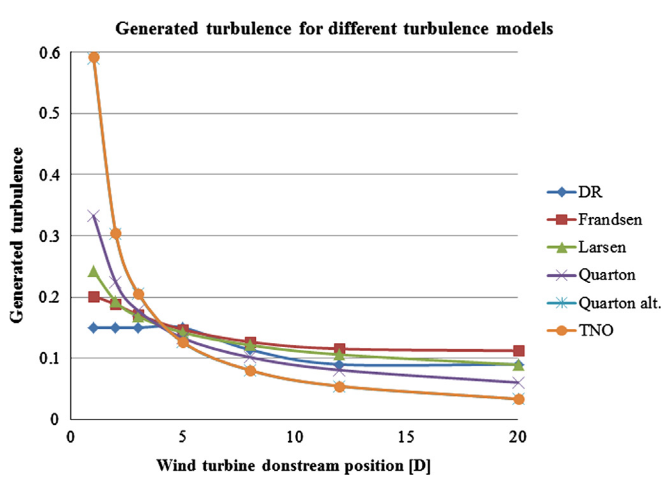


Fig. 1. Development of the generated turbulence downstream a single turbine for different turbulence models.

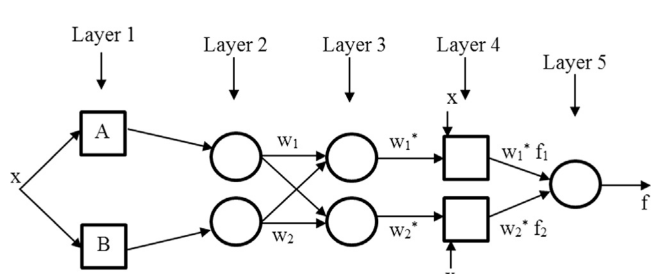


Fig. 2. ANFIS structure.

3. Adaptive neuro-fuzzy application

In this section will be explained application of ANFIS for estimation of wake added turbulence according to the five presented methods. Fuzzy Inference System (FIS) is the main core of ANFIS. FIS is based on expertise expressed in terms of 'IF-THEN' rules and can thus be employed to predict the behavior of many uncertain systems. FIS advantage is that it does not require knowledge of the underlying physical process as a precondition for its application. Thus ANFIS integrates the fuzzy inference system with a back-propagation learning algorithm of neural network. The basic structure of a FIS consists of three conceptual components: a rule base, which contains a selection of fuzzy rules; a database, which defines the membership functions (MFs) used in the fuzzy rules; and a reasoning mechanism, which performs the inference procedure upon the rules and the given facts to derive a reasonable output or conclusion. These intelligent systems combine knowledge, technique and methodologies from various sources. They possess human-like expertise within a specific domain—adapt

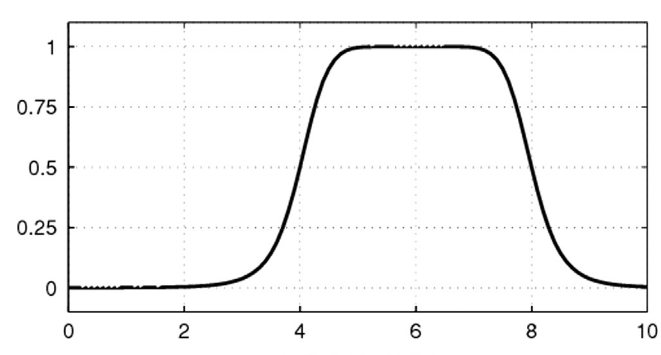


Fig. 3. Bell-shaped membership function ($a=2$, $b=4$, $c=6$).

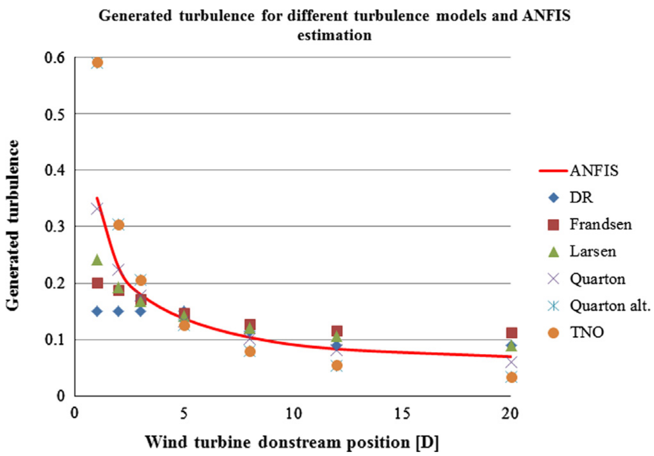


Fig. 4. ANFIS predicted results of the wake added turbulence in comparison with the five methods.

themselves and learn to do better in changing environments. In ANFIS, neural networks recognize patterns, and help adaptation to environments. ANFIS is tuned with a back propagation algorithm based on the collection of input–output data.

ANFIS model will be established in this study to estimate wake added turbulence according to the five presented methods. The ANFIS networks should determine the optimal wake added turbulence for a given number of data inputs. Fuzzy logic toolbox in MATLAB was used for the entire process of training and evaluation of fuzzy inference system. Fig. 2 shows an ANFIS structure with one input, x. X represents wind turbine downstream distance in the wind farm. As training data for ANFIS we used results from five presented methods for turbulence calculation.

In this work, the first-order Sugeno model with two inputs and fuzzy IF-THEN rules of Takagi and Sugeno's type is used:

$$\text{if } x \text{ is } A \text{ then } f_1 = p_1 x + t \tag{15}$$

The first layer consists of input variables membership functions (MFs). This layer just supplies the input values to the next layer. The input is true wind turbine downstream distance in the wind farm. In the first layer every node is an adaptive node with a node function

$$O = \mu(x, y, z),$$

where $\mu(x, y, z)_i$ are MFs.

In this study, bell-shaped MFs (3) with maximum equal to 1 and minimum equal to 0 is chosen

$$f(x; a, b, c) = \frac{1}{1 + ((x - c)/a)^{2b}} \tag{16}$$

where the bell-shaped function depends on three parameters a, b and c. The parameter b is usually positive. The parameter c located the center of the curve as it is shown in Fig. 3.

The second layer (membership layer) checks for the weights of each MFs. It receives the input values from the 1st layer and acts as MFs to represent the fuzzy sets of the respective input variables. Every node in the second layer is non-adaptive and this layer multiplies the incoming signals and sends the product out like

$$w_i = \mu(x)_i \times \mu(x)_{i+1} \tag{17}$$

Each node output represents the firing strength of a rule or weight.

The third layer is called the rule layer. Each node (each neuron) in this layer performs the pre-condition matching of the fuzzy rules, i.e. they compute the activation level of each rule, the number of layers being equal to the number of fuzzy rules. Each node of these layers calculates the weights which are normalized. The third layer is also non-adaptive and every node calculates the ratio of the rule's firing strength to the sum of all rules' firing strengths like

$$w_i^* = \frac{w_i}{w_1 + w_2} \tag{18}$$

$i = 1, 2.$

The outputs of this layer are called normalized firing strenghts or normalized weights.

The fourth layer is called the defuzzification layer and it provides the output values resulting from the inference of rules. Every node in the fourth layer is an adaptive node with node function

$$O_i^4 = w_i^* x f = w_i^*(p_i x + q_i y + r_i) \tag{19}$$

where $\{p_i,\ q_i, r\}$ is the parameter set and in this layer is referred to as consequent parameters.

The fifth layer is called the output layer which sums up all the inputs coming from the fourth layer and transforms the fuzzy classification results into a crisp (binary). The output represents estimated modulation transfer function of the optical system. The single node in the fifth layer is not adaptive and this node computes the overall output as the summation of all incoming signals

$$O_i^4 = \sum_i w_i^* x f = \frac{\sum_i w_i f}{\sum_i w_i} \tag{20}$$

The hybrid learning algorithms were applied to identify the parameters in the ANFIS architectures. In the forward pass of the hybrid learning algorithm, functional signals go forward until Layer 4 and the consequent parameters are indentified by the least squares estimate. In the backward pass, the error rates propagate backwards and the premise parameters are updated by the gradient descent.

4. ANFIS results

At the beginning the ANFIS network was trained with extracted data by above presented analytical methods. The ANFIS network determines optimal wake added turbulence based on the methods and in depend on wind turbine downstream distance in wind farm. The RMS error for the ANFIS network after training procedure was 0.073053. Three bell-shaped membership functions were used to fuzzify the ANFIS input.

After training process the ANFIS networks were tested. Fig. 4 shows the result of the testing of the first ANFIS network. The red solid line represent ANFIS prediction of the wake added turbulence while the analytical methods are also depicted in Fig. 4. It can be concluded that ANFIS makes average estimation of the five used methods.

5. Conclusions

During the last decades, wind turbines have been installed in large wind farms. The grouping of turbines in farms introduces two major issues: reduced power production, because of wake velocity deficits, and increased dynamic loads on the blades, because of higher turbulence levels. This increase in turbulence intensity in wakes behind wind turbines can imply a significant reduction in the fatigue lifetime of wind turbines placed in wakes. Appropriate turbulence calculations should be made before selecting the proper turbine design. The wake added turbulence may be

calculated using different wake or turbulence models. These models are typically very different in detailing level and also in accuracy.

In this work, a novel ANFIS method has been presented and tested for developing an alternative method to predict wake added turbulence. The unique approach of this ANFIS method has been validated against the most commonly used turbulence models. The results show that the ANFIS can be an alternative to the turbulence models. The ANFIS approach predicts the wake added turbulence distribution faster than the analytical methods.

This new ANFIS method is compared with five the most common methods, Danish Recommendation (DR), Frandsen & DIBt, D.C. Quarton, TNO laboratory, Alternative Empirical Approach and G.C. Larsen. It is worth to indicate that superiority of ANFIS method over other methods can be obviously seen with estimation capability of turbulence distribution. Then it is concluded that ANFIS method is very suitable and efficient in order to estimate wake added turbulence for wind energy applications.

Simulations were run in MATLAB and the results were observed on the corresponding output blocks. The main advantages of the ANFIS scheme are: computationally efficient, well-adaptable with optimization and adaptive techniques. The developed strategy is not only simple, but also reliable and may be easy to implement in real time applications using some interfacing cards like the dSPACE, data acquisition cards, NI cards, etc. for control of various parameters. This can also be combined with expert systems and rough sets for other applications. ANFIS can also be used with systems handling more complex parameters. Another advantage of ANFIS is its speed of operation; the tedious task of training membership functions is done in ANFIS.

Acknowledgments

This paper is supported by Project Grant TP35005 “Research and development of new generation wind turbines of high-energy efficiency” (2011–2014) financed by Ministry of Education, Science and Technological Development, Republic of Serbia. This work is also funded by the Malaysian Ministry of Education under the University of Malaya High Impact Research Grant UM.C/625/1/HIR/MoE/FCSIT/03.

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